**Supplementary Information**

**Crop Modeling**



**Figure S1**. Climate change impact on US potatoes (A) and tomatoes (B) for **2050s (2041-2070)**. The baseline is 1981-2010. The maps show the ensemble median yield changes (%) from 5 crop models + 1 statistical model (3 crop models + 1 statistical model for tomatoes) with 5 global climate model simulations for each CRD without adaptations. The boxplots show the regionally changes (%) of water demand (transpiration from sowing to harvest, simulations from 1 crop model\*5 global climate models), nutrients uptake for total biomass [nitrogen + phosphorus + potassium; simulations from 5 (3 for tomato) crop models\*5 global climate models] and yield with earlier planting adaptations [simulations from 5 crop models (3 for tomato) + 1 statistical model \*5 global climate models].



**Figure S1**. **(A)** Baseline simulated versus reported dry yield for US potatoes and tomatoes. Simulations are the ensemble [5 crop models for potato; 4 (1 is a statistical model) for tomato] means±standard errors. Observed potato yields from Monfreda et al. (2008) for year 2000 were increased by 3.6 t/ha to reflect yield potential of more recent years, based on a comparison of several variety trial yields from recent years with the year 2000 data. As Fresno and Yolo (CA) had extremely low reported yields in (Monfreda et al., 2008), we replaced the yields for these two counties with nearby variety trial yields. Observed tomato dry yields are from state statistics (only available for CA and MI). The reported data have been used for calibration by some of the modeling groups (SIMPLE, CropSyst and Substor). **(B)** and **(C)** are same as **(A)**, but the comparison is for potato and the observations are from county stats and variety trails respectively. **(D)** Observed and simulated CO2 effect on potato tuber dry yield. X axis represents the year, and the numbers in the bracket indicate the CO2 changes relative to the baseline. Observations are from recent FACE experiments (Bindi et al., 1998; Bindi et al., 1999; De Temmerman et al., 2002; Miglietta et al., 1998). The outlier (47.6%) for the CO2 effect is from Bindi et al. (1999). Simulations are the ensemble [6 crop models (1 is a statistical model)] means±standard errors. The EPIC model runs with constant CO2 concentration for 2030s and 2050s, so the results were included as two points in the figure.



**Figure S2**. Climate change impact on US potatoes (A) and tomatoes (B) for **2030s (2021-2050)**. The baseline is 1981-2010. The maps show the ensemble median yield changes (%) from 5 crop models + 1 statistical model (3 crop models + 1 statistical model for tomatoes) with 5 global climate model simulations for each CRD without adaptations. The boxplots show the regionally changes (%) of water demand (transpiration from sowing to harvest, simulations from 1 crop model\*5 global climate models), nutrients uptake for total biomass [nitrogen + phosphorus + potassium; simulations from 5 (3 for tomato) crop models\*5 global climate models] and yield with earlier planting adaptations [simulations from 5 crop models (3 for tomato) + 1 statistical model \*5 global climate models].

**Description of individual crop models**

**CropSyst model**

In this study, CropSyst was used for both potato and tomato simulations. CropSyst, a generic crop model, has been evaluated and applied for the simulation of multiple crops at different world locations (Stockle et al. (2014). The model was applied to study the environmental impact of a potato-winter wheat-maize rotation in the US Pacific Northwest, in which potato crop parameters were calibrated using 6 years of field experimental data, and the average simulated yields and coefficient of variations after calibration were similar to commercial yields reported in the region (Peralta and Stockle, 2002). Montoya et al. (2018) conducted a detailed field evaluation of CropSyst at Albacete, Spain based on a two-year potato experiment including four irrigation water treatments (60%, 80%, 100%, and 120% of required irrigation). Not including calibration data, simulated soil water content resulted in Willmott index of agreement (d, which fluctuates between 0 and 1.0, with 1.0 depicting perfect agreement) fluctuating between 0.68 and 0.8 for the different irrigation treatments, d values for evapotranspiration fluctuated from 0.87 to 0.97, while biomass and yield had d values of 0.91 and 0.95, respectively. Lehmann and Finger (2014) optimized management decisions in potato production in the Broye catchment, Switzerland using CropSyst. These authors optimized model crop parameters against local yield records to parameterize a generic potato cultivar that they found representative of the varieties utilized by farmers in the Broye catchment and suitable for their study. Although crop parameterization details were not provided, they followed the same procedure described in detail by Klein et al. (2012) who optimized and validated CropSyst parameters for the simulation of maize in Switzerland.

**DSSAT SUBSTOR-potato model**

The DSSAT SUBSTOR-potato is one of the most used models for potato crop (Raymundo et al., 2014), which was used for potato simulations in this study. The model has been evaluated across a wide range of environments and improvements were implemented to better, simulate the crop response to elevated atmospheric to CO2 and high temperature (Raymundo et al., 2017). The model belongs to a family of crop models in the DSSAT-CSM (Decision Support Systems for Agro-technology Transfer-Crop Simulation Model) software (Hoogenboom et al., 2010; Jones et al., 2003). The model inputs are daily weather data, soil profile parameters, crop management information and cultivar parameters. The SUBSTOR-potato model simulates the daily dynamics of phenology, biomass, and yield accumulation affected by soil water and nitrogen deficit factors (Griffin et al., 1993). The model describes five phenological stages, including pre-planting, planting to sprout elongation, sprout elongation to emergence, emergence to tuber initiation, and tuber initiation to harvest. After emergence, the plant growth is supported by seed resource and when exhausted the potential carbon assimilation is calculated using the radiation use efficiency (RUE) approach. In the model, elevated atmospheric CO2 enhance the daily carbon assimilation (Raymundo et al., 2017) and tuber growth (Ritchie et al., 1998). Crop development and growth are controlled by five cultivar-specific parameters including the effect of photoperiod on tuber initiation (P2, dimensionless), the effect of temperature on tuber initiation (TC, °C), potential leaf growth rate (G2, cm2 m-2 d-1), potential tuber growth rate (G3, g m-2 d-1) and determinacy (PD, dimensionless) (Griffin et al., 1993). This model considers various relative temperature functions to modify potential carbon assimilation, leaf growth, root and tuber growth, and tuber initiation (Griffin et al., 1993).

**EPIC model**

The Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1989), another model used in this study, is a comprehensive biophysical process model that simulates crop biomass, soil processes, and interactions in the cropping system and is capable of capturing the effect of farm management decisions and different climatic condition. EPIC was used for only potato simulations in this study. EPIC has been widely used before for evaluation of agricultural sustainability across the globe but not many studies have evaluated it specifically regarding potato productivity. Wang et al. (2012) evaluated EPIC for soil water estimation as a tool in irrigation scheduling and allocation in a semi-arid region in China. They conducted a long-term field experiment with three rotations (mono winter wheat [MW], mono spring maize [MM] and alfalfa-potato-winter wheat-winter-wheat [APW]). To calibrate the model, they collected specified crop growing data. They reported good accuracy of R2 values for comparing simulated and measured soil water content in different soil layers for all rotations (R2 values for APW and different soil layers were between 0.868 and 0.942). Madaras et al. (2017)) used EPIC to investigate the strategies for soil organic carbon (SOC) improvement in the Czech Republic considering eight-year rotations including 25% potato, 25% clover, and 50% cereals, and they applied four different types of N treatments. They conducted uncertainty analysis to assess the crop yields and SOC predictions’ reliability and showed that almost all of the measurements lied within the model’s uncertainty range. Later they calibrated the model using the observed data from one of the N treatment experiments (only mineral fertilization) and validated it using the data from the remaining N treatment experiments. The model predictions of SOC for non-fertilized treatment were very accurate and in an acceptable range for two other treatments (organic fertilization treatment and a combination of mineral and organic fertilization treatment). Watkins and Lu (1998) studied the environmental and economic consequences of different seed potato rotations (forty-five) in Southeastern Idaho. They calibrated the model using farm-level data for eight years (these data are not presented) and then simulated the yields, N loss, and soil erosion using EPIC while potatoes were in the rotation with spring wheat, feed barley, oats, and canola.

**LINTUL-POTATO-DSS model**

LINTUL-POTATO-DSS, a simple potato simulation model, has been used in several studies to predict end of season potato yields, and was be used for potato simulations in this study. The model is typically used to evaluate potential and actual yields to identify yield gaps and for exploring effects of climate change on yields. The model was used in South Africa to evaluate the efficiency of, among several factors, land use expressed as fresh tuber yield (Steyn et al., 2016). The model’s estimates of fresh tuber yields were in good agreement with the reported national yield, 45 tons/ha compared to 43 tons/ha respectively. In another study in South Africa, the model was used to compare attainable yields with actual yields of a summer crop which ratio is then used to forecast yields of a winter season crop (Machakaire et al., 2016). Yields were forecasted accurately (<20% variation between the actual and forecasted values) early in the growing season. Furthermore, the actual and forecasted yields of the cultivar Innovator were well correlated (r= 0.797) and differences between forecasted and observed yields at harvest were not significant at the 5% level, P=0.637 (t-test). For China, the model was calibrated on field experiments of 2010 and 2011, and validated with independent experimental data of 2011 (Wang et al., 2018). The calibrated model was validated when the simulated potato growing period and tuber dry matter were within +/-15% range of the actual value. The calibrated LINTUL POTATO DSS model was subsequently used to assess the potential of potato production to support China’s food self-sufficiency.

**SIMPLE model**

The recently developedSIMPLE model from the University of Florida is another tool that has been used in this study (Zhao et al., 2018a) for potato and tomato production, which is a simple generic crop model adaptable for any crop to simulate crop development, yield and water dynamics. It was calibrated and evaluated for 14 crops from 17 sites considering 70 treatments (yield RRMSE=25.4% and R2= 0.87, total biomass RRMSE=25.7%). It is also capable of capturing increasing atmospheric CO2 concentration and temperature in C3, C4, and legume crops. The calibrated model was used for regional simulation of irrigated potato tuber dry matter in the Pacific Northwest. The results for year 2000 were compared with reported yields from (Monfreda et al., 2008), where the RRMSE at grid level (0.5\*0.5 degree) was 13.9% and it was able to simulate the spatial yield variability, it showed a well accuracy.

**Statistical model**

Statistical models have been widely used to understand the crop yield response to climate (Holzkämper et al., 2012; Tack et al., 2015) and to make predictions of future yield changes (Lobell et al., 2008; Urban et al., 2012) as well as quantifying the effects of warming (Tack et al., 2015) and assessing effectiveness of crop adaptation options (Butler and Huybers, 2013). A statistical model was used here for potato and tomato yield predictions. The statistical models used monthly maximum and minimum temperature during the growing season to predict county-level and yield. All temperature predictors in the model were in quadratic form to account for non-linear yield response. The model was trained using all available county-level yield observation data for 1981 to 2016 from USDA NASS ([https://quickstats.nass.usda.gov](https://urldefense.proofpoint.com/v2/url?u=https-3A__quickstats.nass.usda.gov&d=DwMFaQ&c=pZJPUDQ3SB9JplYbifm4nt2lEVG5pWx2KikqINpWlZM&r=kJzGguiakSfTWC9wktIklEjwn-UgqV9uEYaN1l_G79g&m=FhGS08Se6zQ_Xpm2O_xglFqGJUZ-3DSzdKHkbheH8xM&s=7F0rOzV3nTjgYZDaE6HEDZLK-bDoVNkHYJqqvWjyy0w&e=)), and historical monthly temperature data from PRISM ([http://prism.oregonstate.edu/](https://urldefense.proofpoint.com/v2/url?u=http-3A__prism.oregonstate.edu_&d=DwMFaQ&c=pZJPUDQ3SB9JplYbifm4nt2lEVG5pWx2KikqINpWlZM&r=kJzGguiakSfTWC9wktIklEjwn-UgqV9uEYaN1l_G79g&m=FhGS08Se6zQ_Xpm2O_xglFqGJUZ-3DSzdKHkbheH8xM&s=hkqLtOwcWbTEl2RJHWkdwFD18Eop_QsPjvVGcyCxCOE&e=)). Prior to model training, yield was converted to yield anomaly (by subtracting a quadratic yearly trend) to remove the long-term yield trend. For each state where yield observation data is available, its growing season month was defined by plant and harvest dates compiled from USDA reports (USDA, 1997; USDA, 2010) and the modeling protocol (Zhao et al., 2018b), and then applied to all counties within the state. Since growing season length varies from 4 to 6 months across states, we trained three different models that used 4, 5, 6 months of temperature data as predictors, respectively. To make yield prediction, the trained model was applied to counties of interest by using future temperature projection as predictors, and the resulting predicted yield anomaly after adding up with baseline yield gives the final yield prediction. The baseline yield for potatoes is from the protocol (Zhao et al., 2018b) and for tomatoes is the model ensemble mean yield. To account for the CO2 fertilization effect on yield, a prescribed CO2-induced yield increase was added to the final predicted yield, which is 10% and 9% yield increase per 100 ppm relative to 360 ppm for potatoes (Miglietta et al., 1998) and tomatoes (Slack et al., 1988), respectively. For adaptation scenario, one-month earlier planting was applied to yield prediction.

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**Economic Modeling**

Data Overview

For economic models it is preferred to have 30 years of annual historical data that is based on annual statistically sound samples and that capture each segment in the supply chain. Rarely does this occur but in the case of fruits and vegetables the data sets are somewhat further from this goal. There are three primary reasons for this. The first is that there are fewer acres of fruits and vegetables grown when compared with row crops such as corn, soybeans, or wheat. Second, there is considerable variance in varieties and quality even within a single species. Third, in this study we have zoomed into the crop reporting district (CRD) level on the supply side to closely monitor the impact of weather on crop production. Even the supply data at the CRD level is only sporadically available with some CRD’s left unreported due to the risks of disclosing an individual producer’s information. In addition, yields and production are sometimes left unreported in some CRD’s because the estimates may be unreliable due to small sample size with high variance.

***Area, Yield, and Production***

Unlike row crops, the majority of fruits and vegetables are produced in large volumes in relatively few geographic areas. In some of those areas the number of producers are few resulting in USDA’s NASS grouping counties or even not reporting production below the state level. Census data shows that all states have a least small amounts of fruit and vegetable production but US production is dominated by California, Florida, Washington, Oregon, and Idaho. Fruit and vegetable production is so important in California that many of the counties complete their own annual estimates of production. Some Florida counties produce their own annual estimates of orange production. Outside of California and Florida, county or sub-state estimates are limited to agricultural census years.

***Prices***

There is considerable data available from the USDA’s Agricultural Marketing Service (AMS) on prices by size and quality for each type of fruit and vegetable in the fresh wholesale market as well as at the farmgate. Consumer prices paid for fresh fruit and vegetables are also relatively available. On the processing side, farmgate prices are also reported but wholesale prices for the processed goods are not generally reported.

***Production Inputs***

In USDA’s Quick Stats database, data on nitrogen, phosphate, and potash application rates for potatoes and tomatoes have been collected for selected states on an annual basis sporadically. Unfortunately, this data is inconsistent with the production practices reported by growers and extension experts. In general, the USDA application rates are significantly lower than those reported by growers and extension experts. As a result, we utilized the fruit and vegetable production budgets compiled by extension experts in each state after reviewing these with growers to ensure current production practices were accurately reflected.

***Costs of Production***

USDA does not conduct a formal survey of fruit and vegetable costs of production like they do for row crops. Subsequently we have relied on fruit and vegetable budgets created the Extension service in each state. Even these cost of production budgets are not available for all years, geographies, or by fresh versus processed use. In this study, these budgets were assembled for the years 2000 to 2017 to provide a base of historical data. If a budget was missing for a historical year, WAEES utilized the input quantities from the last year available multiplied by the input prices for the missing historical year. This provides reasonable estimates of the cost of production since the quantity of inputs used does not usually vary significantly from year to year. Emphasis was placed on assessing the costs of production in 2018 to ensure that the input quantities reflected current production practices. The input quantities were reviewed by extension personnel in Washington and Florida and adjustments were made as suggested.

***Demand & Trade***

U.S. consumer demand for fresh and process fruits and vegetables is based on USDA’s Economic Research Service data sets. The annual data are presented in a time series format and include data on production, imports, exports, and domestic consumption. Due to the perishability of many fruit and vegetables, beginning and ending stock data is often not included in the dataset. In the case of processed products, supply and demand information is occasionally broken up into frozen, dehydrated, and canned products. In the case of potatoes, supply and demand information also includes chipping potatoes.

***International Data***

Supply, demand, and price data on international production of fruits and vegetables by crop can be found in the United Nations’ Food and Agricultural Organization database known as FAOSTAT. Under the “Production” domain, the “Crops” database includes estimates of area harvested, yield, and production by country over the 1961-2017 period for most countries. Historical data on imports and exports by crop is taken from the “Trade” domain, the “Crops and livestock products” database, which includes data from 1961 to 2016. Under the domain, “Food Balance”, the “Commodity Balances-Crops Primary Equivalent” database includes supply and demand data from 1961 to 2013. Although this database includes a demand breakout for processed use, this data has been found to be unreliable. As a result, the demand for fresh and processed by crop is modelled as one demand instead of two demands. As applicable, the commodity balances sometimes include the change in stocks. This data is utilized when it is reported.

General Overview of the Fruit and Vegetable Modeling Framework

Partial equilibrium models are typically broken down into the components of supply and demand which define the structure of the model. In the case of fruits and vegetables, the critical supply components are area, yield, production, and occasionally imports. The critical components of demand are typically food use, exports, and, if the commodity is not too perishable, ending stocks. An important difference from row crops is that many fruits and vegetables are grown specifically for processing or specifically for fresh consumption. Varieties have been developed specific to each of these uses and therefore, substitution across the processed and fresh sectors is very limited or often nonexistent. The implication for economic models is that crops produced for the fresh sector are really a different commodity than the same type of crop produced for the processing sector. This also implies that processed product prices will likely not have the same variance as fresh product prices. Even though the diagram below shows the fresh and processed sectors for a given crop, it actually represents two different commodities.

In addition to the basic components of supply and demand, the diagram below shows some of the basic drivers of supply and demand in the blue and yellow boxes. For the most part, these are the standard drivers derived for economic theory. However, there is an important physical constraint that applies to nearly all fruits and vegetables and that is available irrigation water. With the exception of a few potatoes in Colorado, all commercial production of fruits and vegetables is irrigated. Constraints on available water would cause producers to optimize their water use to those crops with the highest return per unit of water use.

Figure 1 is a single country representation for a single fruit or vegetable commodity. In partial equilibrium models, the model solves by changing the price to balance supply and demand. If demand is higher than supply, the price will increase causing demand to decrease and, depending on biological lags, the supply to decrease to bring the market into equilibrium.

The problem becomes more complex as additional countries are added. To the extent that fresh fruits and vegetables are somewhat homogenous, the law of one price tends to prevail. Certainly, there are market distortions such as tariffs and exchange rates which cause prices to move differently across countries. Yet even with these distortions, prices are related across markets with the exception of the extreme case when a country does not trade. With the presence of trade, the equilibrium price level in a given country is determine not only by its own supply, demand, and policies, but also by the supply, demand, and policies in all trading countries.

Figure 2 illustrates how the partial equilibrium models solve with multiple countries involved. At the top of the diagram, Country 1 is the residual supplying country. The choice of this country is usually based on the largest exporter with the fewest policy distortions affecting trade or production. This choice is based on convenience, not necessity because it doesn’t really matter which country it is. The model begins with an assumption about the level of trade which will be replaced after the first iteration. Based on the initial trade assumption and the domestic supply and demand equations, the model will solve for the farm price that balances supply and demand in the residual supplying country. The farm price is translated to the port price in the residual supplying country through a price linkage equation that captures transportation cost to the port. The residual supplying country’s port price is then linked to the port prices in other countries through a price linkage equation for each port price that captures, exchange rates, transportation costs, and tariffs. The port price is then translated into farm prices accounting for transportation costs as well as export tariffs or other domestic policies. Based on these prices, each country determines it domestic supply and demand as well as its net trade position. The net trade positions are summed across all countries to get a new trade path for the residual supplying country replacing the original assumption completing the first iteration. The second iteration begins by solving for a new price level in the residual supplier country which is then translated to through transportation costs, tariffs, and exchange rates to the port price in other countries following the same process used in the first iteration. The model continues to iterate until supply and demand is balanced in each country and globally. This process is used to solve each year in the forecast horizon.

US Potato Model Structure

In the United States, potatoes are produced in three seasons including spring, summer, and fall. The fall season captures over 90 percent of total potato production. Total potato supply is determined by the sum of imports, production, and beginning stocks.

US potato demand is initially divided into those potatoes which are sold (93%) and those that are not (7%). For those potatoes which are sold demand is broken down into fresh use (25.7%), processing use (61.1%), feed use (0.2%), and seed use (6.0%). For those potatoes which are not sold

In some fruits and vegetables there are multiple processed products that are produced. Whether the fruit or vegetable is processed or fresh, consumer demand for food use is driven by inflation adjusted income, population, tastes and preferences, inflation adjusted own price, and where appropriate, inflation adjusted substitute prices. Exchange rates can also significantly affect the fruit or vegetable prices when a significant portion is traded.

Crop area harvested is driven by the expected net returns for the crop and water availability. Expected net returns are calculated as the product of expected price and expected yield less the expected cost of production. Crop yield is driven by gains in technology and growing conditions. Production is determined as the product of crop area and yield.

US Tomato Model Structure

In commercial tomatoes production, tomatoes are produced either for the fresh market or the processed market, but they are not interchanged between the markets. Specific varieties are produced for the fresh market that insure shelf life while processed tomato varities target specific processing charateristics.

**Economic Modeling Details**

***General Modeling Approach***

The models used for this analysis are global partial equilibrium models with behavioral equations that measure the responsiveness of growers to economic incentives to produce as well the responsiveness of consumers to prices and income. Unlike optimization models, partial equilibrium models do not maximize or minimize an objective function subject to a set of constraints and therefore do not produce corner solutions that must be further constrained to limit changes to relevant ranges. Instead, measures of past responsiveness of producers and consumers to economic incentives are captured through the estimated equations. Changes in economic incentives result in producer and consumer responses in the context of how they responded to the incentives in the past. This responsiveness is measured in economics by elasticities. The larger the elasticity the more responsive the producer or consumer to the economic incentives.

In this analysis, the partial equilibrium models simultaneously solve for each commodity’s price that balances supply and demand globally. In addition, the model includes the added complexity of irrigation water constraints in the United States. To determine how the irrigation water will be allocated, the net return per gallon of water is calculated for the irrigated fruits and vegetables as well as row crops. If the irrigation water constraint is binding, then either irrigated land must be reduced or the producer must be willing to reduce applied water and subsequently yields. Given relatively thin margins for row crops, it is unlikely that water applications rates would be reduced because of the negative yield impacts. In the case of fruits and vegetables, it is also assumed that producers would reduce crop area rather than reduce water application rates. In this analysis, binding water constraints result only in reduced crop area. This is captured in the model through another set of simultaneous equations which effectively equilibrate on the supply and demand for irrigation water. The supply of irrigation water is an exogenous variable supplied from the IFPRI models and scaled to the CRD level by Washington State University. The demand for water is determined by

Where the variables are defined as:

Ai: Acreage for irrigated crop i

Ri: Water application rate for crop i

i: Irrigated crops for i = 1 to m irrigated crops

Effr: Basin efficiency of basin r, where r is an element of 1 to b basins.

WD: Irrigation water demand

The water application rates and basin efficiency by crop are derived from the IFPRI model scenarios. Irrigated crop area is estimated by the model in iterative steps. In the first step, irrigated crop area by crop is estimated without irrigation water constraints. Total irrigation water demand is then calculated across crops via the irrigation water demand equation above. If the total irrigation water demand is less than the irrigation water supply available, irrigated area levels by crop remain at the estimates provided in the first step. However, if irrigation water demand is greater than the irrigation water supply, then model enters an iterative process to solve for a crop area adjustment for each crop.

Step 1:

Ai = f(ENRi, Ai,t-1)

ENRi = E[Pi]\*E[Yi] – E[Ci]

Where the additional variables are defined as:

Ai: Acreage for irrigated crop i

Ai,t-1: Acreage of irrigated crop i in the previous year

ENRi: Expected net returns, crop i  
Pi: Expected price of crop i  
Yi: Expected yield of crop i  
Ci: Expected variable cost of producing crop i   
WS: Total water available for irrigation

Is WD ≤ WS? If so, irrigated crop area estimation stops at step 1.

Step 2:

If WD > WS, then the second iterative process begins which includes step 2 and step 3. The simplest approach would be to reduce the irrigated acres across all crops by the same percentage until the irrigation water demanded equals irrigation water supply (step 2). But some crops are more profitable so we must also account for the likelihood that less profitable crops will likely be more impacted by water constraints (step 3). However, it is also unlikely that only the least profitable crops will be impacted because some farmers may not produce all crops but still have a water allocation.

Returning to simple process in step 2, the model uses equilibration to solve for a generic level of adjustment (k) for irrigated crop area that would make irrigation water demand equal to irrigation water supply. The process is similar to price equilibration except that the model will not increase irrigated crop area if irrigated water demand is less than irrigated water supply (k=1 in this case). The model calculates changes in k based on (water supply – water demand)\*dampening factor. The size of the dampening factor is usually relatively small (0.00001) so that changes in k are very small in each iteration. The starting value for k is 1. If water supply is greater than or equal to water demand, k stays at 1. If not, this means (water supply – water demand ) is less than zero. If the difference were -100 and using the dampening factor above, the adjustment to k would be -0.001 producing a k value of 0.999.

In the third step, another set of equations is invoked. These equations estimate the amount by which the original level of crop acres in step 1 must be adjusted in order to comply with the irrigation constraint. Since the value of irrigation water varies by crop, the model first calculates the revenue per unit of water applied. These revenues per unit of water applied are used to estimate the amount by which each crop areas must be adjusted to comply with the constraint. Each crop area has its own adjustment that depends on the deflated gross revenue per unit of water applied for the own crop but also competing crops. In order to show this as an equation, we added the element o, which is an element of the index i, in order to show the context of the own crop relative to the competing crops.

AAi = k\*λi\*Ai

Where the additional variables are defined as:

AAi: Actual irrigated crop area from crop i  
k: General adjustment to crop area to that would make irrigation water demand equal to  
 irrigation water supply  
i: Irrigated crop i in the set of i = 1 to m irrigated crops   
o: Irrigated crop o, referring to the own crop, in the set of i = 1 to m irrigated crops  
λo: Specific adjustment to k for the own crop, where o represents the own crop in the set of  
 m irrigated crops. There is a total of m different λi’s. Note that 0≤ λi≤1.

***Model Specification***

Crop Area Equations

Relative to row crops, crop area devoted to fruits and vegetables is very small. As a result, crop area does not really compete among fruit and vegetables in a significant way. Fruit and vegetable net returns are significantly higher than row crop net per acres eliminating competition with row crop area. Discussion with fruit and vegetable growers bears this out with all growers indicating that having a profitable production contract is the primary driver followed occasionally by irrigation water access constraints. For annual crops, growers prioritize fruit and vegetables over other crops for both land area and irrigation. Based on grower discussions, they indicate that profitability (usually driven by the commodity price listed in the contract) is the key driver.

Yields

Irrigation Water Availability Constraints

***Estimation Technique***

***Interaction with Other Disciplines and Models***

Figure 7 illustrates the interaction of the interaction of the data flows from the other disciplines into the economic model.

Extension Teams

The extension teams at Washington State and University of Florida have been critical in documenting current production practices, cropping patterns, reviewing and revising costs of production, providing irrigation insights and irrigation water demands, and helping to identify the participants in the fruit and vegetable supply chain. The costs of production, water constraints, cropping patterns and market structure information are direct inputs into economic models.

As discussed previously, costs of production feed directly into the calculation of expected net returns which drive the number crop acres planted. Irrigation water supply available to crops directly constrains the quantity of irrigated crops that can be planted. The expected net returns per unit of irrigation water applied directly impacts the mix of irrigated crops that are planted.

IFPRI Team

The International Food Policy Research Institute (IFPRI) has used its global agricultural model (IMPACT) to evaluate the impacts of potential climate projections on global agriculture. In this process, they evaluated key issues such as water availability and water consumption by crop. Specifically, they developed scenarios using all 5 GCM’s (GFDL-ESM2M, HadGEM2-ES365, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M), the RCP 8.5 greenhouse gas concentration pathway, and the SSP2 socio-economic pathway scenario. The average across the 5 GCM’s under the RCP 8.5 greenhouse gas scenario was used.

Researchers at Washington State downscaled the IFPRI data from the 12 watersheds spanning the US to derive estimates of the water availability constraints by crop reporting district (CRD) as per the requirements of the economic model. This process is documented in the report entitled, “Protocol for Downscaling of Hydrology Data for US Fruit and Vegetable Modeling” by Kirti Rajagopalan, Claudio O. Stöckle, Tim Sulser, and Dave Gustafson.

From the IFPRI data, the irrigation water application rates can also be derived. For the 8 specialty crops included in this study, the irrigation requirements per acre by crop are provided by the IFPRI modeling results.

Crop Model Team

The crop modeling team provides the impacts on yields, fertilizer inputs, and water demand for the eight crops included in the study. The crop models always assume all inputs are available for optimal yield with the exception of temperature. Under the alternative climate scenarios, with and without adaptation, the crop model team provides the impact of yields, fertilizer update, and water demand.

Arkansas LCA Team

The Arkansas life cycle analysis team will provide data on the fertilizer efficiency for the 8 crops included in the study. Fertilizer efficiency is defined as the ratio of fertilizer uptake by the plant divided by actual fertilizer application rates.

The crop modeling team provides the fertilizer uptake to attain optimal yields to the economic model. However, the economic models use actual yields per harvested acre as reported by NASS. Therefore, the fertilizer application rate to attain the optimal yields must be adjusted to reflect the actual yields and fertilizer efficiency. Fertilizer uptake to attain optimal yield (provided by the crop models) is multiplied by ratio of actual yields to optimal yields and by fertilizer efficiency.

**Table S1. Counties Selected for Crop Modeling[[1]](#footnote-1)**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **State** | **Crop Reporting District (CRD)** | **Target Crop Area in the CRD (ha)** | **County** | **Target Crop Area in the County (ha)** |
| Arizona | AZ80 | 7,223 | Maricopa | 3,173 |
| California | CA51 | 186,624 | Fresno | 59,003 |
| California | CA80 | 35,381 | Imperial | 11,168 |
| California | CA40 | 24,658 | Monterey | 15,228 |
| California | CA50 | 32,326 | Yolo | 16,223 |
| Colorado | CO80 | 22,900 | Rio Grande | 7,438 |
| Florida | FL80 | 181,203 | Hendry | 41,242 |
| Florida | FL50 | 64,226 | Polk | 29,880 |
| Florida | FL50 | 64,226 | St. Johns[[2]](#footnote-2) | 6,020 |
| Georgia | GA70 | 10,002 | Decatur | 6,264 |
| Idaho | ID90 | 100,707 | Bingham | 31,262 |
| Idaho | ID70 | 7,275 | Canyon | 3,143 |
| Idaho | ID80 | 35,569 | Minidoka | 12,770 |
| Maine | ME10 | 23,205 | Aroostook | 23,205 |
| Michigan | MI50 | 9,746 | Montcalm | 7,230 |
| Michigan | MI80 | 6,240 | St. Joseph | 3,748 |
| Minnesota | MN90 | 12,464 | Dakota | 3,505 |
| Minnesota | MN80 | 12,763 | Freeborn | 2,512 |
| Minnesota | MN40 | 6,460 | Otter Tail | 4,266 |
| Minnesota | MN50 | 22,859 | Renville | 9,813 |
| New York | NY40 | 19,728 | Genesee | 4,295 |
| North Dakota | ND30 | 25,906 | Walsh | 13,448 |
| Oregon | OR10 | 16,180 | Marion | 6,932 |
| Oregon | OR30 | 10,380 | Umatilla | 7,788 |
| Texas | TX97 | 7,291 | Hidalgo | 6,601 |
| Washington | WA20 | 27,984 | Benton | 25,024 |
| Washington | WA50 | 63,672 | Grant | 30,033 |
| Washington | WA10 | 9,899 | Skagit | 5,515 |
| Washington | WA90 | 7,152 | Walla Walla | 6,990 |
| Wisconsin | WI60 | 6,307 | Fond du Lac | 2,052 |
| Wisconsin | WI30 | 9,361 | Langlade | 6,596 |
| Wisconsin | WI50 | 55,503 | Portage | 26,549 |

**Table S2.** Crop models used for potato simulations.

|  |  |
| --- | --- |
| **Crop model/Statistical model** | **Reference** |
| SIMPLE | Zhao et al. (2019) |
| CropSyst | Stöckle et al. (1994) |
| LINTUL-POTATO-DSS | Haverkort et al. (2015) |
| EPIC | Williams et al. (1989) |
| CSM-Substor-Potato | Raymundo et al. (2017) |
| Statistical model | Li et al. (2019) |

**Table S3.** General circulation models (GCM) used for future scenarios.

|  |
| --- |
| **GCM** |
| GFDL-ESM2M |
| HadGEM2-ES365 |
| IPSL-CM5A-LR |
| MIROC-ESM-CHEM |
| NorESM1-M |

**Table S4.** Yearly atmospheric CO2 concentration for the baseline (1981-2010) and future period (2030s and 2050s) under RCP8.5 scenario.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Baseline** | | **2030s** | | **2050s** | |
| Year | CO2 (ppm) | Year | CO2 (ppm) | Year | CO2 (ppm) |
| 1981 | 340 | 2021 | 419 | 2041 | 494 |
| 1982 | 341 | 2022 | 422 | 2042 | 499 |
| 1983 | 342 | 2023 | 425 | 2043 | 504 |
| 1984 | 344 | 2024 | 428 | 2044 | 508 |
| 1985 | 345 | 2025 | 431 | 2045 | 513 |
| 1986 | 347 | 2026 | 435 | 2046 | 519 |
| 1987 | 349 | 2027 | 438 | 2047 | 524 |
| 1988 | 351 | 2028 | 442 | 2048 | 529 |
| 1989 | 352 | 2029 | 445 | 2049 | 535 |
| 1990 | 354 | 2030 | 449 | 2050 | 541 |
| 1991 | 355 | 2031 | 452 | 2051 | 546 |
| 1992 | 356 | 2032 | 456 | 2052 | 552 |
| 1993 | 357 | 2033 | 460 | 2053 | 558 |
| 1994 | 358 | 2034 | 464 | 2054 | 564 |
| 1995 | 360 | 2035 | 468 | 2055 | 571 |
| 1996 | 361 | 2036 | 472 | 2056 | 577 |
| 1997 | 363 | 2037 | 476 | 2057 | 583 |
| 1998 | 365 | 2038 | 481 | 2058 | 590 |
| 1999 | 367 | 2039 | 485 | 2059 | 597 |
| 2000 | 369 | 2040 | 489 | 2060 | 604 |
| 2001 | 370 | 2041 | 494 | 2061 | 611 |
| 2002 | 373 | 2042 | 499 | 2062 | 618 |
| 2003 | 375 | 2043 | 504 | 2063 | 625 |
| 2004 | 377 | 2044 | 508 | 2064 | 632 |
| 2005 | 379 | 2045 | 513 | 2065 | 639 |
| 2006 | 381 | 2046 | 519 | 2066 | 647 |
| 2007 | 383 | 2047 | 524 | 2067 | 654 |
| 2008 | 385 | 2048 | 529 | 2068 | 662 |
| 2009 | 387 | 2049 | 535 | 2069 | 669 |
| 2010 | 389 | 2050 | 541 | 2070 | 677 |

**Hydrology Data Downscaling Methodology**

Total annual irrigation water supply and crop water utilization estimates for the period 2005 to 2050 are available from the IMPACT model (Robinson et al. 2015) at the scale of Food Production Units (FPU’s). For the lower 48 states of the US there are 14 such FPU’s, which correspond to relatively large watersheds (see Figure 1). Associated integrated modeling efforts (crop, economic, life cycle assessment) typically operate at a finer geographic scale (e.g. county or Crop Reporting District, CRD), thus a downscaling method is required in order to translate the IMPACT hydrology estimates down to such smaller geographic units of analysis.

Multiple water availability variables are reported by IMPACT. The specific variable to be utilized within this study for water availability is irrigation water supplied (variable name: *giwd\_s\_fpu; units billions of cubic meters), which is the ideal irrigation water demands constrained to the total capacity of the system to meet demands*. The variable to be used for crop water requirements is the ideal crop water demand under no water stress and no loss assumptions (variable name: *iwd; units: mm)*. Losses in the system are considered through a basin efficiency fraction assumption (variable name: basineffx00; units: no units) which varies over time to account for improvements in efficiencies over time. This FPU level efficiency assumption captures all possible inefficiencies/losses in the system including those related to inefficient irrigation technologies and losses in delivery canals.

For consistency with other modeling efforts, the data to be selected include those for all 5 GCM’s (GFDL-ESM2M, HadGEM2-ES365, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M), the RCP 8.5 greenhouse gas concentration pathway, and the SSP2 socio-economic pathway scenario. The irrigation water supply estimates consider future demands constrained to the total water capacity in each FPU. This is generally an upper bound of irrigation supply, as policy changes that restrict irrigation water use – such as restrictions on ground water pumping in California (e.g. the Sustainable Groundwater Management Act of 2014) – are not incorporated in these results.

DOWNSCALING METHODOLOGY

Downscaling is based on scaling factors calculated from total irrigation withdrawal estimates in the 2015 USGS Water Use Data (Dieter et al. 2018), which are at the county scale. The assumption is that “relative” withdrawal estimates across counties contained within an FPU are an approximation of the relative redistribution of supply accounting for hydrology (climate, topography, soil etc.) and human infrastructure effects (such as inter-basin transfer of water). It is also assumed that these same redistributions hold true in the future. While this downscaling captures the major variations in of supply, given that the USGS dataset is survey based, there could be biases in some counties. Figure 2 shows the variability in magnitude of irrigation withdrawals at a county level. FPU boundaries are also displayed. Figure 3 shows this variability aggregated to a CRD level. For CRDs of interest to this study, it was confirmed from state-level and local-agency reports that the major irrigation water use areas have been assigned the largest scaling factors.

Figure 4 shows the range of irrigation scaling factors within the nine FPU’s of interest for this study. The results show that there is one CRD in California that uses about half the share of irrigation supply within that FPU. The sum of all irrigation scaling factors within an FPU is 1.

Figure 5 shows the range of irrigation scaling factors for the 31 CRD’s included in this study. These same data are listed in tabular form in Appendix 1. The results show that the one CRD highlighted previously in California is indeed one of the CRD’s included in this study.

Individual crop irrigation water requirements are also based on estimates from the IMPACT model and are assumed to be the same for all CRDs within an FPU.

**References for Downscaling Methodology**

1. Dieter, C.A., Linsey, K.S., Caldwell, R.R., Harris, M.A., Ivahnenko, T.I., Lovelace, J.K., Maupin, M.A., and Barber, N.L., 2018, Estimated use of water in the United States county-level data for 2015 (ver. 2.0, June 2018): U.S. Geological Survey data release, https://doi.org/10.5066/F7TB15V5.
2. Robinson, Sherman; Mason d'Croz, Daniel; Islam, Shahnila; Sulser, Timothy B.; Robertson, Richard D.; Zhu, Tingju; Gueneau, Arthur; Pitois, Gauthier; and Rosegrant, Mark W. 2015. The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT): Model description for version 3. IFPRI Discussion Paper 1483. Washington, D.C.: International Food Policy Research Institute (IFPRI). http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/129825.
3. SGMA, 2014. Sustainable Groundwater Management Act of 2014, State of California, <https://water.ca.gov/Programs/Groundwater-Management/SGMA-Groundwater-Management>.

**Appendix S1. Irrigation Scaling Factors for all 31 CRD’s in this Study**

|  |  |  |
| --- | --- | --- |
| **ST-CRD** | **FPU** | **ScalingFactor** |
| 640 | California | 0.0442 |
| 650 | California | 0.2532 |
| 651 | California | 0.4923 |
| 680 | California | 0.1029 |
| 480 | Colorado | 0.3413 |
| 680 | Colorado | 0.0773 |
| 880 | Colorado | 0.0062 |
| 1670 | Columbia | 0.1534 |
| 1680 | Columbia | 0.2175 |
| 1690 | Columbia | 0.208 |
| 4110 | Columbia | 0.047 |
| 4130 | Columbia | 0.0395 |
| 5310 | Columbia | 0.0051 |
| 5320 | Columbia | 0.0413 |
| 5350 | Columbia | 0.0637 |
| 5390 | Columbia | 0.005 |
| 2650 | GreatLakes | 0.1376 |
| 2680 | GreatLakes | 0.2 |
| 3640 | GreatLakes | 0.0327 |
| 5550 | GreatLakes | 0.0011 |
| 2740 | Mississippi | 0.0003 |
| 2750 | Mississippi | 0.0049 |
| 2780 | Mississippi | 0 |
| 2790 | Mississippi | 0.0013 |
| 5530 | Mississippi | 0.0015 |
| 5550 | Mississippi | 0.0191 |
| 2310 | Northeast | 0.007 |
| 2740 | RedWinnipeg | 0.3969 |
| 2750 | RedWinnipeg | 0.0723 |
| 2780 | RedWinnipeg | 0.0264 |
| 2790 | RedWinnipeg | 0.0017 |
| 3830 | RedWinnipeg | 0.0463 |
| 880 | RioGrande | 0.3364 |
| 4897 | RioGrande | 0.1103 |
| 1250 | Southeast | 0.1076 |
| 1280 | Southeast | 0.4878 |
| 1370 | Southeast | 0.0936 |

1. Note: Not all eight target crops (carrots, green beans, oranges, potatoes, spinach, strawberries, sweet corn, and tomatoes) can be grown in all 31 of these counties. Counties where open-field production is not possible (e.g. oranges in northern areas) will not be included in the modeling protocol for that crop. [↑](#footnote-ref-1)
2. St. Johns County included to ensure representative modeling of potatoes in northern Florida. [↑](#footnote-ref-2)